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Efficiency of the Czech banking sector employing the DEA window analysis approach

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Abstract

The aim of this paper is to apply the Data Envelopment Analysis (DEA) window analysis on the data of the Czech commercial banks and to examine the efficiency of the Czech banking sector during the period 2003–2012. The paper employed an extended DEA approach, specifically DEA window analysis for the efficiency assessment of commercial banks in the Czech Republic. It is based on panel data for the period from 2003 to 2012. Data Envelopment Analysis has become a popular approach in measuring the efficiency of banking industry. We use the DEA window analysis based on an input oriented model to measure banking efficiency. In the analysed period, the average efficiency under constant return to scale reached 70–78 % and average efficiency under variable return to scale reached 84–89 %. The most efficient bank was GE Money Bank and the lowest efficient bank was Československá obchodní banka. The group of large bank (Československá obchodní banka, Česka spořitelna and Komerční banka) was lower efficient than other banks in the banking industry. The reasons of the inefficiency of the group of large banks were the excess of deposits in balance sheet and inappropriate size of operation.

Keywords: Data Envelopment Analysis; window analysis; Czech banking sector; commercial bank

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1. Introduction

The Czech financial system is characterized as a bank-based system, thus, banks play an important role in the economy. The transformation and consolidation of the Czech banking sector was carried out during the 1990s. From 1998–2001, a second round of privatization occurred with the sale to foreigners of majority equity interests in four large Czech banks (Československá obchodní banka, Česká spořitelna, Komerční banka and Investiční a poštovní banka). These Big Three (Československá obchodní banka, Česká spořitelna and Komerční banka) are still the dominant players in the market. Their combined market share in terms of assets is about 50 % and they have an extensive networks of branches. From 2003–2012, the number of banks was almost constant. In 2012, the number of banking institutions included 18 banks (four large banks, eight medium-sized banks and six small banks), five building societies and 20 foreign bank branches. There were several mergers and acquisitions in the Czech banking market during the years analyzed. The Czech banking sector has an almost stable shareholder structure. The Czech Republic joined the European Union (EU) in 2004 and in 2009 the small and open Czech economy was hit hard by the global financial and economic crisis. Thanks to its very strong deposit base and the very small percentage of loans denominated in foreign currency, the banking sector remained stable throughout the global financial crisis.

The aim of this paper is to apply the Data Envelopment Analysis (DEA) window analysis on the data of the Czech commercial banks and to examine the efficiency of the Czech banking sector during the period 2003–2012. The paper employed an extended DEA approach, specifically DEA window analysis for the efficiency assessment of commercial banks in the Czech Republic. It is based on panel data for the period from 2003 to 2012. Data envelopment analysis has become a popular approach in measuring the efficiency of banking industry. We use the DEA window analysis based on an input oriented model to measure banking efficiency. The contribution should be able to see the bank efficiency evolves over time and to see whether any size effect exists in the banking efficiency. This analysis provides trends of efficiency and the rank of each bank evaluated in terms of its effectiveness. The obtained results allow for an analyses of trends of the overall banking sector efficiency. By this approach, the technical efficiency is analyzed sequentially with a certain window width (i.e. the number of years in a window) using a panel data of the commercial domestic banks. The main idea is to capture the temporal impact on bank technical efficiency and see its short-run evolution from one window to another, in particular the pure technical efficiency and scale efficiency. It is the first application of the window analysis on the Czech commercial banks during the period 2003–2012.

The structure of the paper is follow. Next section describes empirical literature about banking efficiency in the Czech Republic. Third section presents the methodology of DEA window analysis and section 4 describe data and selection of variables. Next part of paper reveals the estimated results and last section concluded the paper.

2. Literature review

Several empirical analyses of the efficiency of the Czech banking sector exist and we refer to some of them. Most empirical studies evaluated banking efficiency in the 1990s and the authors investigated whether private banks were more efficient than state-owned banks. For example, Taci and Zampieri (1998) found that private banks have a higher mean efficiency score, supporting rapid privatization.

Bonin et al. (2005) found that foreign-owned banks were most efficient and government-owned banks were least efficient. The results of Matoušek and Taci (2005) indicated that foreign banks were on average more efficient than other banks, although their efficiency was comparable with the efficiency of 'good' small banks in the early years of their operation.

Weill (2003) found a positive influence of foreign ownership on the cost efficiency of banks in the Czech Republic and Poland. His conclusion was that the degree of openness of the banking sector to foreign capital has a positive impact on performance. It may also have a positive influence on the macroeconomic performance of these countries, because of the important role of the banking sector in the financing of these economies.

Fries and Taci (2005) found that banking systems in which foreign-owned banks have a larger share of total assets have lower costs and that the association between a country's progress in banking reform and cost efficiency is non-linear. Early stages of reform were associated with cost reductions, while costs tend to rise at more advanced stages. They argued that private banks are more efficient than state-owned banks, but there are also differences among private banks. Privatised banks with majority foreign ownership were the most efficient and those with domestic ownership were the least. The results of Andries and Cocris (2010) showed that banks in the Czech Republic are inefficient from the perspective of costs. To improve efficiency, banks need to improve the quality of assets owned by improving the lending process and reducing the share of nonperforming loans.

Stavárek and Polouček (2004) estimated efficiency and profitability in selected banking sectors, including the Czech Republic. They found that Central European Countries were less efficient than their counterparts in European Union member countries. They also found that the Czech and Hungarian banking sectors were on average evaluated as the most efficient and the Czech banking sector showed itself as the most aligned banking industry among transition countries. Their conclusion was a refutation of the conventional wisdom that foreign-owned banks are more efficient than domestic-owned banks, and that size is one of the factors that determines efficiency. To achieve greater efficiency, a bank should be large, well-known, easily accessible and offer a wide range of products and services, or if small, must focus on specific market segments, offering special products. Any other structure leads to lower relative efficiency for the bank.

Stavárek (2005) estimated commercial bank efficiency in the group of Visegrad countries (Czech Republic, Hungary, Poland, Slovakia) before joining the EU. A Stochastic Frontier Approach and Data Envelopment Analysis were applied to data from the period 1999–2003. He concluded that the Czech banking sector is the most efficient, followed by the Hungarian with a marginal gap. Although there has been an improvement in levels of efficiency in all countries since 1999, its intensity was not sufficient to converge with Western European banking sectors.

Staněk (2010) compared the efficiency of the banking sector in the Czech Republic and Austria. The SFA was employed to measure the efficiency of the banking sector. It was found that the efficiency of the Czech banking sector has improved in the last ten years and come closer to the efficiency of the Austrian banking sector.

Also, Staníčková and Skokan (2012) evaluated the banking sector of the Czech Republic as highly efficient. Stavárek and Řepková (2012) found that efficiency increased in the period 2000–2010 and they found that the largest banks perform significantly worse than medium-sized and small banks.

There is a lack of studies in the Czech Republic examining banking efficiency using Dynamic Data Envelopment Analysis, which creates an opportunity for this research. The network structure of Data Envelopment Analysis models was applied to Czech banks by Jablonský (2012).

3. The brief of methodology

The study of the efficient frontier began with Farrell (1957), who defined a simple measure of a firm's efficiency that could account for multiples inputs. The term Data Envelopment Analysis was originally introduced by Charnes et al. (1978) based on the research of Farrell (1957). DEA is a non-parametric linear programming approach, capable of handling multiple inputs as well as multiple outputs (Asmild et al., 2004).

This methodology allows handling different types of input and output together. A DEA model can be constructed either to minimize inputs or to maximize outputs. An input orientation objects at reducing the input amounts as much as possible while keeping at least the present output levels, while an output orientation aims at maximizing output levels without increasing the use of inputs. (Cooper et al., 2000).

Data Envelopment Analysis is a mathematical programming technique that measures the efficiency of a decision-making unit (DMU) relative to other similar DMUs with the simple restriction that all DMUs lie on or below the efficiency frontier (Seiford and Thrall, 1990). DEA measures the relative efficiency of a homogeneous set of decision-making units in their use of multiple inputs to produce multiple outputs. DEA also identifies, for inefficient DMUs, the sources and level of inefficiency for each of the inputs and output (Charnes et al., 1995). It provides a means of comparing the efficiency of DMUs with each other based on several inputs and / or outputs. It derives its name from a theoretical efficient frontier which envelops all empirically-observed DMUs.

This analysis is concerned with understanding how each DMU performs relative to others, the causes of inefficiency, and how a DMU can improve its performance to become efficient. In that sense, the focus of the methodology should be on each individual DMU rather than on the averages of the whole body of DMUs. DEA calculates the relative efficiency of each DMU in relation to all the other DMUs by using the actual observed values for the inputs and outputs of each DMU. It also identifies, for inefficient DMUs, the sources and level of inefficiency for each of the inputs and outputs (Charnes, et al., 1995).

The CCR model is the basic DEA model, as introduced by Charnes et al. (1978) and then it was modified by Banker et al. (1984) and became the BCC model, which accommodates variable returns to scale. The CCR (Charnes, Cooper, Rhodes) model presupposes that there is no significant relationship between the scale of operations and efficiency by assuming constant returns to scale (CRS) and delivery of overall technical efficiency. The CRS assumption is only justifiable when all DMUs are operating at an optimal scale. However, firms or DMUs in practice might face either economies or diseconomies to scale. Banker et al. (1984) extended the CCR model by relaxing the CRS assumption. The resulting BCC (Banker, Charnes, Cooper) model was used to assess the efficiency of DMUs characterized by variable returns to scale (VRS). The VRS assumption provides the measurement of pure technical efficiency (PTE), which is the measurement of technical efficiency devoid of scale efficiency (SE) effects. If there appears to be a difference between the TE and PTE scores of a particular DMU, then it indicates the existence of scale inefficiency (Sufian, 2007).

As e.g. Sathye (2003) showed, the DEA has some limitations. When the integrity of data has been violated, DEA results cannot be interpreted with confidence. Another caveat of DEA is that those DMUs indicated as efficient are only efficient in relation to others in the sample. It may be possible for a unit outside the sample to achieve higher efficiency than the best practice DMU in the sample. Knowing which efficient banks are most comparable to the inefficient bank enables the analyst to develop an understanding of the nature of inefficiencies and reallocate scarce resources to improve productivity. This feature of DEA is clearly a useful decision-making tool in benchmarking. As a matter of sound managerial practice, profitability measures should be compared with DEA results and significant disagreements investigated.

Data Envelopment Analysis is performed in only one time period, hampering the measurement of efficiency changes when there is more than one time period. A DEA model is sometimes applied on a repeated basis, e.g. the so-called window analysis method (Charnes et al., 1995) when a panel data set comprising both time series and cross-section samples is available, but this produces little more than a continuum of static results, when in fact a static perspective may be inappropriate (Sengupta, 1996).

Window analysis is one of the methods used to verify productivity change over time. As Savić et al. (2012) showed, window analysis technique works on the principle of moving averages (Charnes et al., 1995; Yue, 1992; Cooper et al. 2007). DEA window analysis was proposed by Charnes et al. (1985) in order to measure efficiency in cross sectional and time varying data. Thus, it is useful in detecting performance trends of a decision making unit over time. Each DMU (i.e. bank) is treated as a different bank in a different period which can increase the number of data point. In the other word, each DMU in a different period is treated as if it were a different DMU (independent) but remain comparable in the same window (Cooper et al., 2011). Such capability in the case of a small number of DMUs and a large number of inputs and outputs would increase the discriminatory power of the DEA models (Cooper et al., 2011). Therefore, small sample sizes problem can be solved. And another advantage of DEA window analysis is that the performance of a bank in a period can be contrasted against themselves and against other banks overtime (Asmild et al., 2004).

The performance of a unit in a particular period is contrasted with its performance in other periods in addition to the performance of other units. This results in an increase in the number of data points in the analysis, which can be useful when dealing with small sample sizes. Varying the window width, that is the number of time periods included in the analysis, means covering the spectrum from contemporaneous analysis, which include only observations from one time period, to intertemporal analysis, which include observations from the whole study period (Paradi et al., 2001). A DEA window analysis, with a window width somewhere between one and all periods in the study horizon, can be viewed as a special case of a sequential analysis. It is assumed, that what was feasible in the past remains feasible, and all previous observations are included. This is not the case in the window analysis, where only observations within a certain number of time periods (i.e. a window) are considered. Once the window is defined the observations within that window are viewed in an intertemporal manner and the analysis is therefore better referred to as locally intertemporal (Tulkens and Vanden Eeckaut, 1995).

The number of firms that can be analyzed using the DEA model is virtually unlimited. Therefore, data on firms in different periods can be incorporated into the analysis by simply treating them as if they represent different firms. In this way, a given firm at a given time can compare its performance at different times and with the performance of other firms at the same and at different times. Through a sequence of such windows, the sensitivity of a firm's efficiency score can be derived for a particular year according to changing conditions and a changing set of reference firms. A firm that is DEA efficient in a given year, regardless of the window, is likely to be truly efficient relative to other firms. Conversely, a firm that is only DEA efficient in a particular window may be efficient solely because of extraneous circumstances. In addition, window analysis provides some evidence of the short-run evolution of efficiency for a firm over time. Of course, comparisons of DEA efficiency scores over extended periods may be misleading (or worse) because of significant changes in technology and the underlying economic structure (Yue, 1992).

Following Asmild et al. (2004) and Gu and Yue (2011), consider N DMUs $(n = 1,2,..,N)$ observed in T $(t = 1,2,\ldots,T)$ periods using r inputs to produce s outputs. Let DMU_n^t represent an DMU_n in period t with a r dimensional input vector $x_n^t = (x_n^{1t}, x_n^{2t}, \ldots, x_n^{n})'$ and s dimensional output vector $y = (y_n^{1t}, y_n^{2t}, \ldots, y_n^{st})'$. If a window starts at time k $(1 \leq k \leq T)$ with window width w $(1 \leq w \leq t-k)$, then the metric of inputs is given as follows:

$$x_{kw} = (x_1^k, x_2^k, \ldots, x_N^k, x_1^{k+1}, x_2^{k+1}, \ldots, x_N^{k+1}, x_1^{k+w}, x_2^{k+w}, \ldots, x_N^{k+w})', \tag{1}$$

The metric of outputs as:

$$y_{kw} = (y_1^k, y_2^k, \ldots, y_N^k, y_1^{k+1}, y_2^{k+1}, \ldots, y_N^{k+1}, y_1^{k+w}, y_2^{k+w}, \ldots, y_N^{k+w})', \tag{2}$$

The CCR model of DEA window problem for DMU_t^k is given by solving the following linear program:

$$\min \theta, \tag{3}$$

subject to

$$\theta' X_t - \lambda' X_{kw} \geq 0, \tag{4}$$

$$\lambda' Y_{kw} - Y_t \geq 0, \tag{5}$$

$$\lambda_n \geq 0 \ (n = 1,2,\ldots,N \times w). \tag{6}$$

BCC model formulation can be obtained by add the restriction $\sum_{n=1}^{n} \lambda_n = 1$ (Banker et al., 1984). The objective value of CCR model is designated technical efficiency and the objective of BCC model is pure technical efficiency. The BCC model is illustrated as:

$$\min \theta, \tag{7}$$

subject to

$$\theta' X_t - \lambda' X_{kw} \geq 0, \tag{8}$$

$$\lambda' Y_{kw} - Y_t \geq 0, \tag{9}$$

$$\sum_{n=1}^{n} \lambda_n = 1, \tag{10}$$

$$\lambda_n \geq 0 \ (n = 1,2,\ldots,N \times w). \tag{11}$$

Asmild et al. (2004) point out that there are no technical changes within each of the windows because all DMUs in each window are compared and contrast against each other and suggest a narrow window width should be used. Charnes et al. (1995) found that w = 3 or 4 tended to yield the best balance of in formativeness and stability of the efficiency scores. In order to be sure that the results will be credible, a narrow window width must be used. Therefore, a 3 year window has been chosen in this paper (*w* = 3).

4. Data and selection of variables

The data set used in this paper was obtained from the database BankScope and the annual reports of commercial banks during the period 2003–2012. All the data is reported on an unconsolidated basis. We analyze only commercial banks that are operating as independent legal entities. As we have reliable data extracted directly from annual reports, we eliminate the risk that incomplete or biased data may distort the estimation results. We use balanced panel data from 11 Czech commercial banks (with regard to mergers and acquisitions of banks).

In order to conduct a DEA window analysis estimation, inputs and outputs need to be defined. Four main approaches (intermediation, production, asset and profit approach) have been developed to define the input-output relationship in financial institution behavior. We adopted an intermediation approach which assumes that the banks' main aim is to transform liabilities (deposits) into loans (assets). Consistent with this approach, we assume that banks collect deposits to transform them, using labor, in loans. We employed two inputs (labor and deposits), and two outputs (loans and net interest income). We measure labor by the total personnel costs covering wages and all associated expenses and deposits by the sum of demand and time deposits from customers, interbank deposits and sources obtained by bonds issued. Loans are measured by the net value of loans to customers and other financial institutions and net interest income (NII) as the difference between interest incomes and interest expenses. Descriptive statistics of inputs and outputs are in Table 1.

Table 1. Descriptive statistics.

	Deposits	Labor	Loans	NII
Mean	168020.35	2254.39	112547.36	6490.35
Median	57913.95	1051.35	47043.25	2343.80
Max	608467.00	8525.00	451471.00	29460.00
Min	351.20	20.50	185.30	32.90
St.Dev.	192182.37	2609.69	122631.65	7757.62

5. Empirical analysis and results

We adopted DEA window analysis SBM (slack based model – non-radial) models that can evaluate the overall efficiency of decision-making units for the whole terms as well as the term efficiencies. We used the DEA window analysis to estimate efficiency under the assumptions of constant and variable returns to scale. For empirical analysis we used MaxDEA software.

Banking efficiency was estimated using DEA window analysis models, especially an input-oriented model with constant returns to scale and input-oriented model with variable returns to scale. The reason for using both techniques is the fact that the assumption of constant returns of scale is accepted only in the event that all production units are operating at optimum size. This assumption, however, is in practice impossible to fill, so in order to solve this problem we calculate also with variable returns of scale (Řepková, 2012). We use panel data of 11 Czech commercial banks (with regard to mergers and acquisitions of banks). Thus, BancoPopolare (POPO) is now Equa bank from 2011, UniCredit Bank (UNIC) was HVB in period 2003–2006, POPO was IC Bank in period 2003–2006, LBBW was Dresdner Bank in 2003 and then it was called Bawag bank in 2004–2007.

The results of the DEA efficiency scores under constant variable of scale are presented in Table 2. Moving average efficiency are shown in three-year window. During the period 2003–2012, the average efficiency calculated using the CRS ranges from 70 % to 78 %. This development shows that Czech banks are on average considered to be efficient, with only marginal changes over time. Thus, the average inefficiency of the Czech banking sector in the CCR model was in range 22–30 %. The reason for the inefficiency of Czech banks is mainly the excess of client deposits on the balance sheet of banks.

Table 2. CCR model.

DMU	2003–2005	2004–2006	2005–2007	2006–2008	2007–2009	2008–2010	2009–2011	2010–2012	Mean
CSOB	0.5141	0.4578	0.4656	0.4908	0.5367	0.5597	0.5829	0.5771	0.5231
CS	0.6348	0.6289	0.6409	0.6684	0.7304	0.7671	0.8581	0.8386	0.7209
KB	0.5982	0.6101	0.6309	0.6280	0.6418	0.6720	0.7227	0.7286	0.6540
UNIC	0.7605	0.8318	0.6865	0.7128	0.7316	0.8446	0.9362	0.9254	0.8037
GEM	0.9666	0.9655	0.9857	1.0000	0.9679	0.9679	0.9861	0.9842	0.9780
RB	0.5980	0.6703	0.6363	0.6674	0.7440	0.7305	0.7994	0.7572	0.7004
POPO	0.6837	0.6850	0.6855	0.6985	0.8036	0.6319	0.5384	0.3200	0.6308
JTB	0.8098	0.9304	0.8888	0.7883	0.7810	0.7855	0.8170	0.7317	0.8166
LBBW	0.6107	0.7062	0.7875	0.9048	0.8560	0.7043	0.5951	0.6214	0.7232
PPF	0.5905	0.5809	0.6733	0.8267	0.9527	0.8970	0.8654	0.9506	0.7921
Volksbank	0.9145	0.8798	0.7848	0.8404	0.8686	0.8569	0.9162	0.9169	0.8723
Mean	0.6983	0.7224	0.7151	0.7478	0.7831	0.7652	0.7834	0.7593	

The results of the efficiency of individual banks show that the most efficient bank were GE Money Bank and then Volksbank and JT Bank. On the other hand, the lowest efficient bank was ČSOB, Banco Popolare and Komerční banka. It can be seen that the group of largest bank (ČSOB, Česká spořitelna and Komerční banka) are lower efficient than other groups of bank. The reason for this inefficiency is that the group of large banks have excess of deposits in balance sheet. Thus, the excess of deposits reflected negatively to net interest income by increasing interest costs of banks.

Table 3. BCC model.

	2003–2005	2004–2006	2005–2007	2006–2008	2007–2009	2008–2010	2009–2011	2010–2012	Mean
CSOB	0.7403	0.6820	0.6667	0.6288	0.6498	0.6627	0.6424	0.6319	0.6631
CS	0.9436	0.9666	0.9602	0.9061	0.9359	0.9790	0.9671	0.9845	0.9554
KB	0.8899	0.9243	0.9599	0.8599	0.8447	0.7991	0.8096	0.8685	0.8695
UNIC	1.0000	0.8548	0.9030	0.9354	0.9332	0.8803	0.9488	0.9262	0.9227
GEM	0.9670	0.9659	0.9859	1.0000	1.0000	0.9778	0.9870	0.9842	0.9835
RB	0.7188	0.7092	0.7936	0.8246	0.9059	0.7401	0.8006	0.7595	0.7815
POPO	0.9605	1.0000	1.0000	0.9556	0.9526	0.8597	0.7597	0.7562	0.9055
JTB	0.8469	0.9454	0.9141	0.8313	0.8201	0.7972	0.8564	0.8267	0.8548
LBBW	0.6566	0.7093	0.7923	0.9079	0.8571	0.7302	0.6603	0.7437	0.7572
PPF	0.6378	0.6113	0.6899	0.8396	0.9727	0.9144	0.8814	0.9930	0.8175
Volksbank	0.9258	0.8837	0.7893	0.8876	0.9575	0.8573	0.9378	0.9496	0.8986
Mean	0.8443	0.8411	0.8595	0.8706	0.8936	0.8362	0.8410	0.8567	

Table 3 presents the efficiency of individual Czech banks calculated under the variable return to scale. The average efficiency calculated in BCC model reached the value from 84 to 89 %. The most efficient banks were GE Money Bank, Česká spořitelna and UniCredit Bank. Also in BCC model, the lowest efficient bank was ČSOB. We conclude the result of Stavárek and Řepková (2012) who applied DEA methodology and found that ČSOB had average efficiency under 50% and the efficiency of ČSOB were decreasing during the period 2003–2010.

We found that the main source of inefficiency was the excess of client deposits managed by banks and also the inappropriate range of operation of large banks. The second argument is confirmed by the calculating scale efficiency of individual banks (Table 4). The efficiency of individual banks, especially technical efficiency, pure technical efficiency and scale efficiency, is shown in Table 4. Scale efficiency is calculated by dividing the technical efficiency calculated under CRS by technical efficiency calculated under VRS.

Table 4. Efficiency of Czech commercial bank.

	Technical Efficiency Score (CRS)	Pure Technical Efficiency Score (VRS)	Scale Efficiency Score
CSOB	0.5231	0.6631	0.7917
CS	0.7209	0.9554	0.7542
KB	0.6540	0.8695	0.7584
UNIC	0.8037	0.9227	0.8736
GEM	0.9780	0.9835	0.9944
RB	0.7004	0.7815	0.9014
POPO	0.6308	0.9055	0.6866
JTB	0.8166	0.8548	0.9544
LBBW	0.7232	0.7572	0.9503
PPF	0.7921	0.8175	0.9662
Volksbank	0.8723	0.8986	0.9715
Mean	0.7468	0.8554	0.8730

When we compare the results of the CCR model and the BCR model we can see that the model with variable returns to scale achieves higher degree of the efficiency than the model with the constant returns to scale. This result is caused by the fact that the BCC model decomposes inefficiency of production units into two components: the pure technical inefficiency and the inefficiency to scale. Values of efficiency computed by VRS reach higher values than efficiency computed by CRS by eliminating the part of the inefficiency that is caused by a lack of size of production units. The mean scale efficiency of the Czech banking sector was 87 % within the period 2003–2012. The highest scale efficient bank was GE Money Bank. GE Money Bank was the highest efficient bank in the Czech banking industry during analyzed period. The lowest value of scale efficiency reached Banco Popolare, it means that Banco Popolare choice inappropriate size. Result of scale efficiency show that the group of large bank achieved low scale efficiency. This confirm that large bank choice inappropriate range of operation.

6. Conclusion

The aim of the paper was to apply the Data Envelopment Analysis window analysis on the data of the Czech commercial banks and to examine the efficiency of the Czech banking sector during the period 2003–2012. We use the DEA window analysis based on an input oriented model to measure banking efficiency. We estimated efficiency under the assumptions of constant and variable returns to scale. In the analysed period, the average efficiency under constant return to scale reached 70–78 % and average efficiency under variable return to scale reached 84–89 %. The most efficient bank was GE Money Bank and the lowest efficient bank was Československá obchodní banka. We found that the group of large bank (Československá obchodní banka, Česka spořitelna and Komerční banka) was lower efficient than other banks in the banking sector. It was probably caused by the fact that these banks had excess of deposits in balance sheet and it reflected negatively to net interest income by increasing interest costs of banks.

Next, we calculated scale efficiency which confirm that other argument of low efficiency of the large banks is inappropriate range of operations. The group of the largest banks achieved lower scale efficiency than other banks in the market. The average scale inefficiency of large banks was about 23 %, which confirm that large banks were too big and one of reasons of inefficiency was scale inefficiency.

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